



Estimating Willingness-to-Pay Under Unobserved Confounders

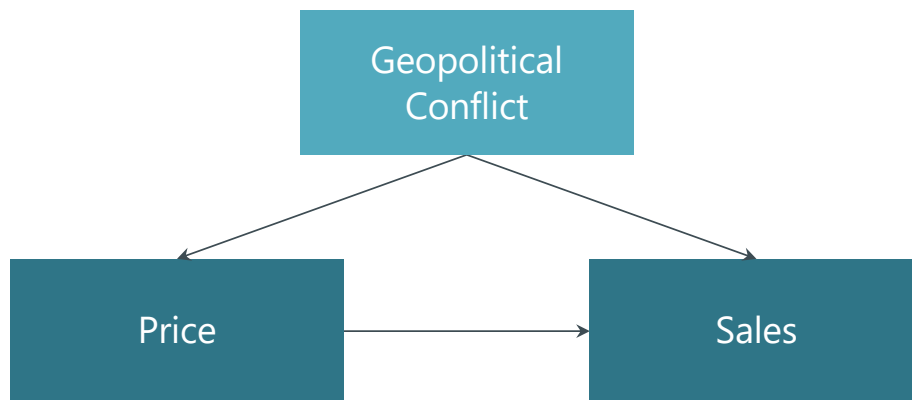
AGIFORS RM SG, April 2025, Warsaw

MARC NIENTKER

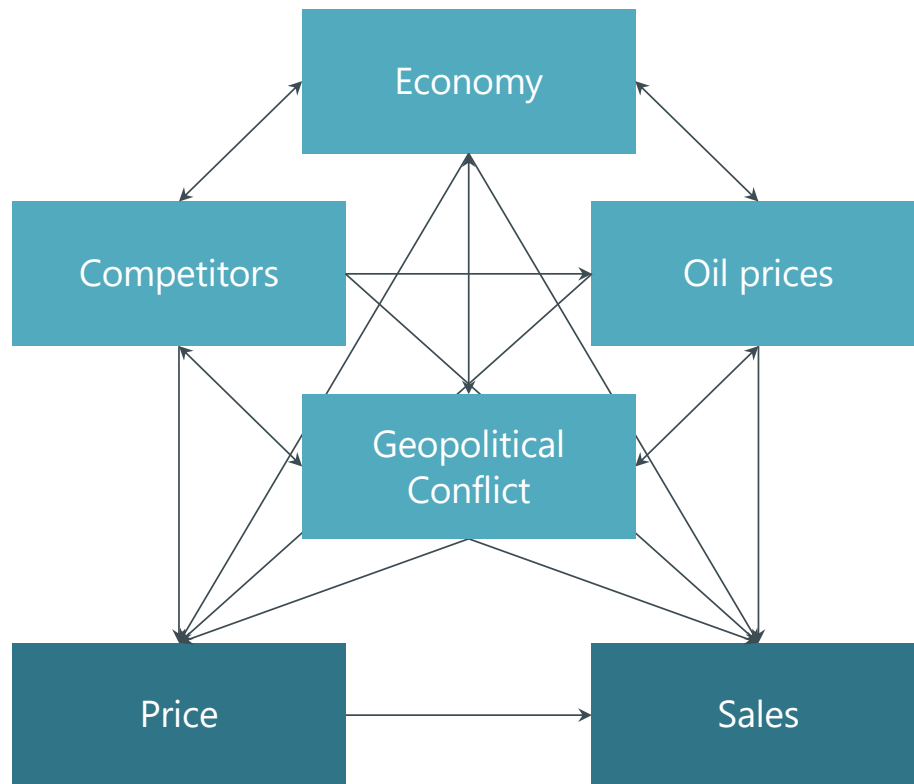
Price elasticity: the complexity of estimating causal effects

Confounders

A confounding factor is something that impacts both price and sales



Price elasticity: the complexity of estimating causal effects



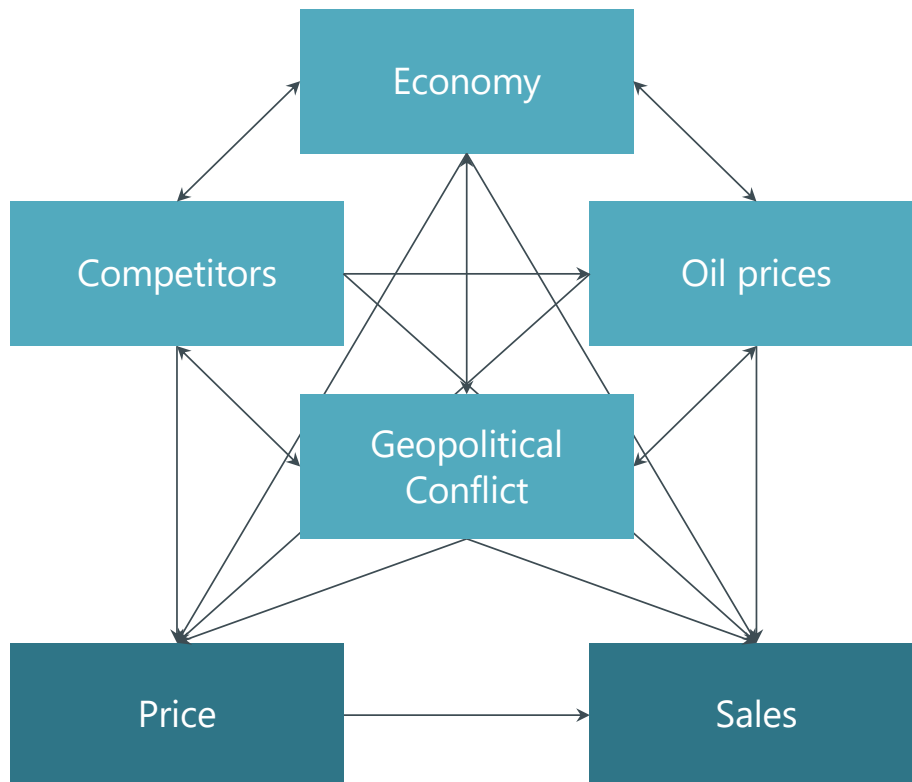
Confounders

A confounding factor is something that impacts both price and sales

The range of potential confounders is vast and often beyond what one might readily anticipate



Price elasticity: the complexity of estimating causal effects



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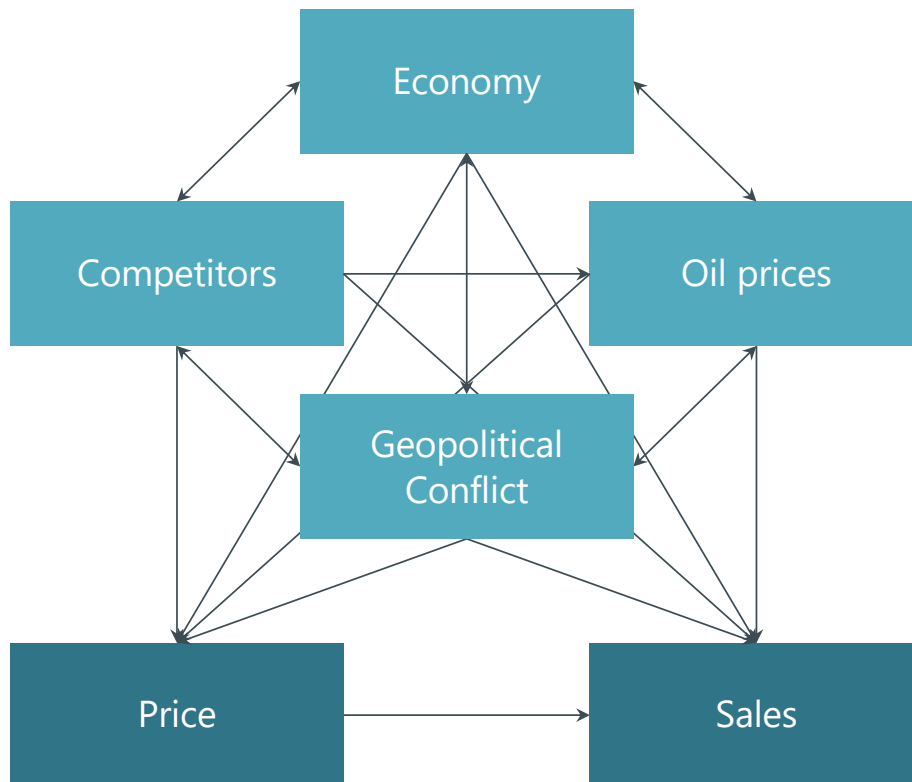
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Omitted variable bias

Missing data on any one confounding variable distorts the observed relationship between price and sales



Price elasticity: the complexity of estimating causal effects



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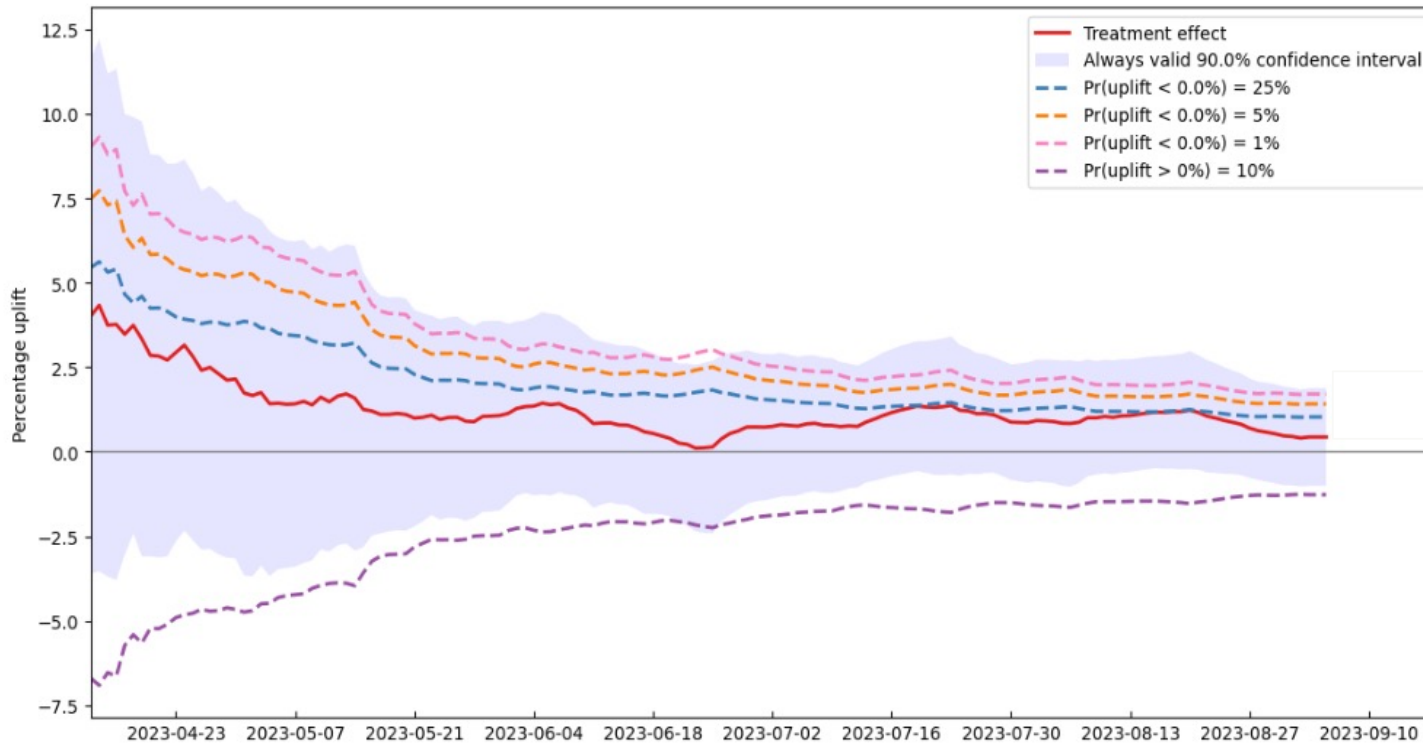
Omitted variable bias

Missing data on any one confounding variable distorts the observed relationship between price and sales

Ignoring missing confounding factors very likely returns under-estimated elasticities



Common approach to deal with confounders – Experimentation



We presented experimentation during last year's AGIFORS RM

Use randomization to correct for confounders and other bias inducing problems

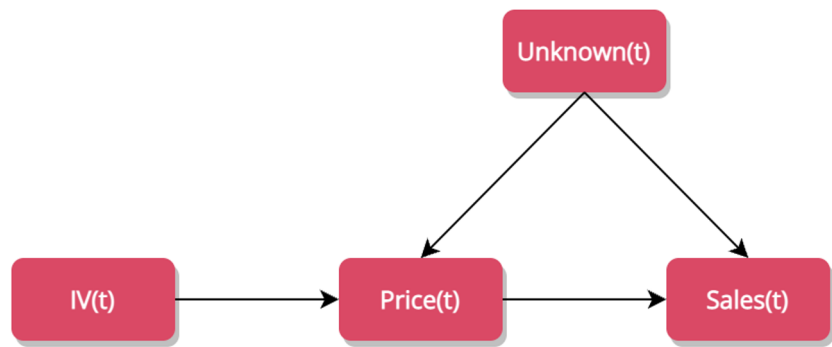
Disadvantages:

- Can be complicated and expensive to implement
- Elasticities change resulting in a continuously ongoing measurement need



Alternative methods to deal with confounders – Observational data

Instrumental variables



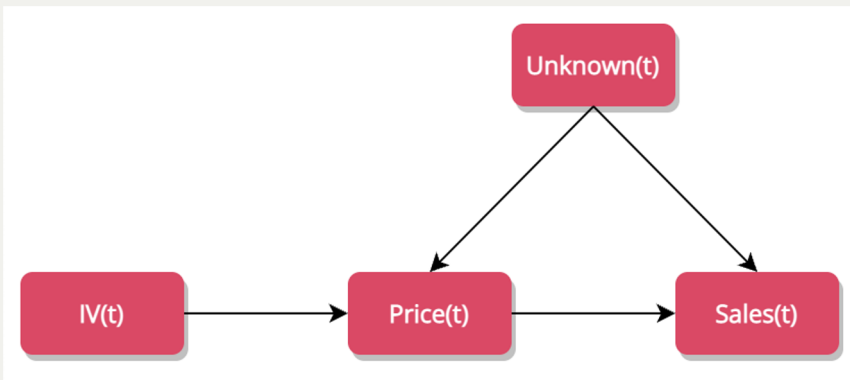
An instrumental variable must be

- Correlated with price (relevance)
- Uncorrelated with booking decisions (validity)



Alternative methods to deal with confounders – Observational data

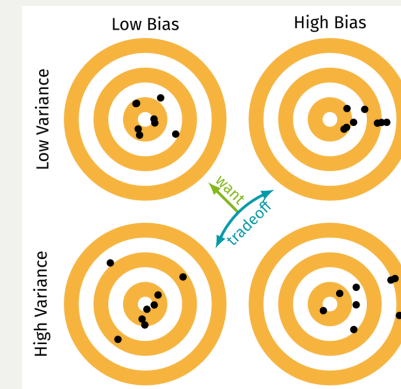
Instrumental variables



An instrumental variable must be

- Correlated with price (relevance)
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Double machine learning



Collect all possible data on potential confounders and control for the bias variance trade-off

Strong assumption: There are **more confounders** than any researcher or team can ever imagine



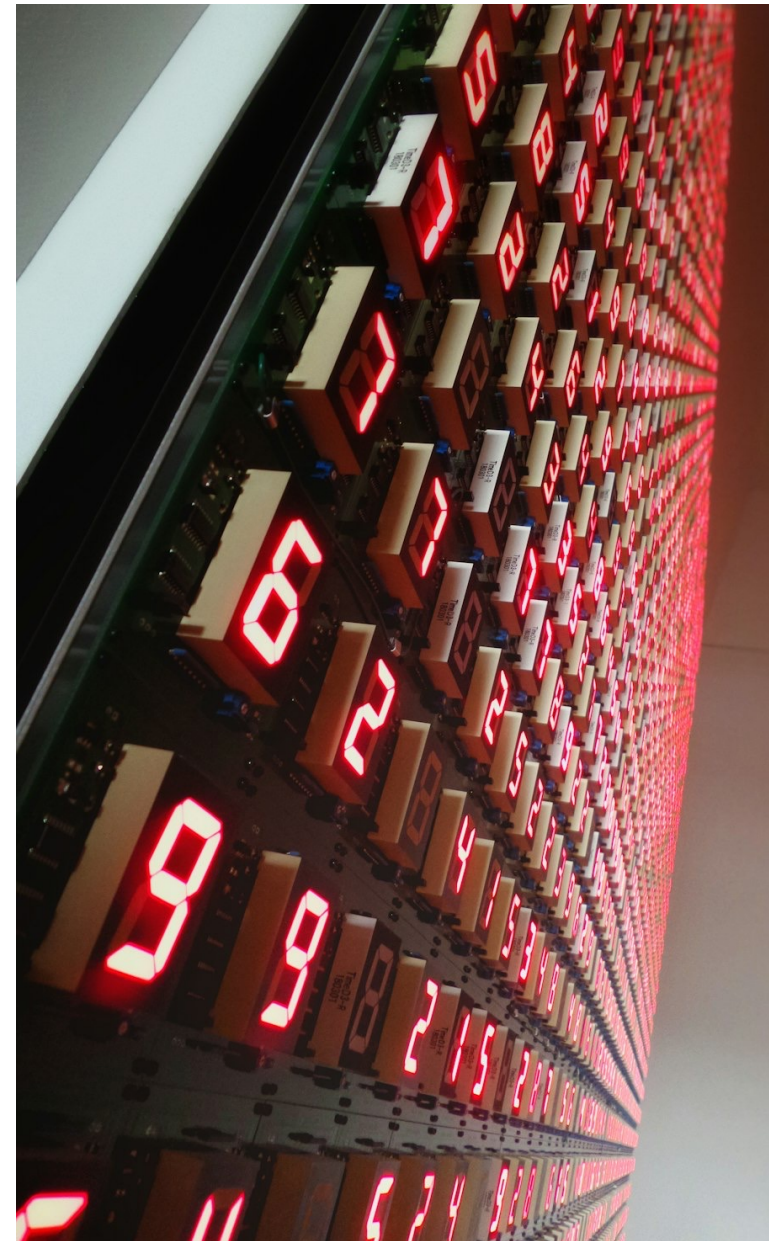
A panel model approach – introduction

The core idea is to directly **include** the presence of **unobserved confounders** in our price elasticity model

Structure data into two dimensions

- **Time dimension:** transaction date
- **Cross sectional dimension:** itinerary / flight
 - Origin – Destination
 - Flight date
 - Departure time

Standard panel model: $s_{it} = p'_{it}\beta + x'_{it}\gamma + \varepsilon_{it}$



A panel model approach – fixed effects

Standard panel model: $s_{it} = p'_{it}\beta + x'_{it}\gamma + \varepsilon_{it}$

Popular since the 70s to include fixed effects parameters:

α_i : unobserved, time-invariant characteristics of each itinerary.

ξ_t : unobserved shocks that are common across all itineraries at a given time.

Panel model (fixed effects): $s_{it} = p'_{it}\beta + x'_{it}\gamma + \alpha_i + \xi_t + \varepsilon_{it}$

Even though the parameters α_i and ξ_t are unobserved, the model can be estimated through demeaning across the time and itinerary dimensions.



A panel model approach – interactive fixed effects

Panel model (fixed effects): $s_{it} = p'_{it}\beta + x'_{it}\gamma + \alpha_i + \xi_t + \varepsilon_{it}$

Homogeneity of time effects is unrealistic in practice:

- Confounders do not have the same effect on all itineraries
- Itineraries react differently to different confounders

Let $f_t = (f_{t1}, \dots, f_{tr})$ represent a set of common confounders (factors) and let $\lambda_i = (\lambda_{i1}, \dots, \lambda_{ir})$ represent their heterogeneous impact (loadings)

Panel model + factor model: $s_{it} = p'_{it}\beta + x'_{it}\gamma + \lambda'_i f_t + \varepsilon_{it}$

Key references

Two seminal papers that defined this field of research:

- **Bai, Jushan (2009)**. "Panel Data Models with Interactive Fixed Effects." *Econometrica*.
- **Pesaran (2006)**. "Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure." *Econometrica*.

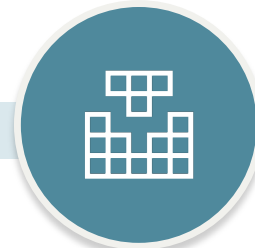


WHY NOW

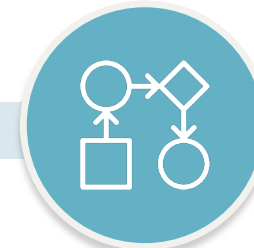
Recent advances make interactive fixed effects practically implementable



Estimation



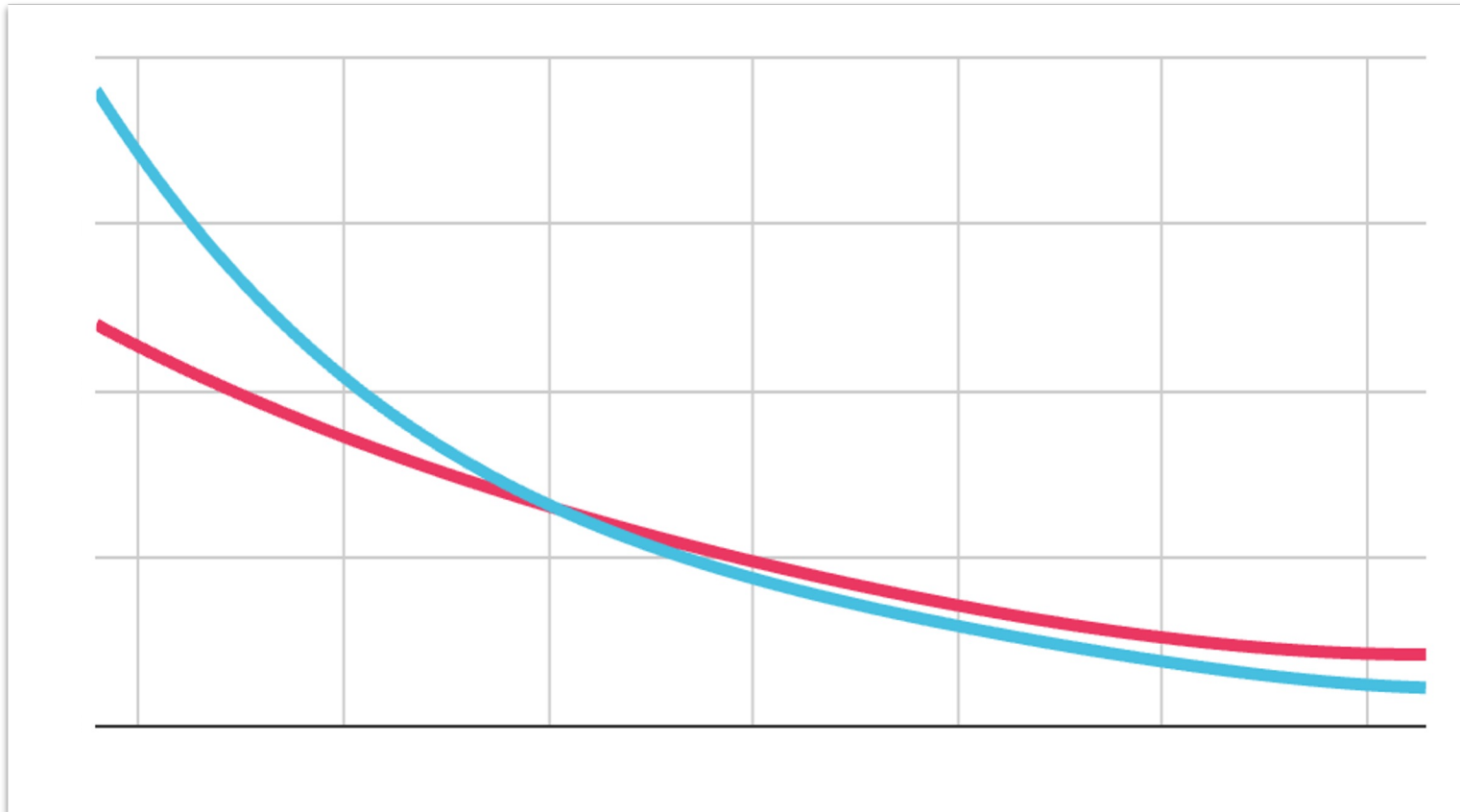
Link functions



High dimensionality



Empirical results showcase significant impact on estimated elasticities



- Panel model without IFE
- Panel model with IFE



Resulting in strong impact validated across the globe & industries



Improve elasticity estimation and demand forecasting

Combining IFE models with demand forecasting models in one causal forecasting framework has improved accuracy by +15% across a variety of clients



Strong impact for our clients

We've implemented our solution globally seeing repeatedly strong results. We believe mostly due to properly identifying causality.



Proven across sectors

We believe in the reliability of the approach. We have applied the same methodology to e-commerce and retail pricing with equally strong results.



where it all **adds up**

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